

AD-A265 637



MENTATION PAGE

Form Approved
OMB No. 0704-0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE April 1993	3. REPORT TYPE AND DATES COVERED professional paper	
4. TITLE AND SUBTITLE AN ANALOG CLUSTERING NETWORK FROM A BIOLOGICAL MODEL		5. FUNDING NUMBERS PR: EE20 PE: 0601153N WU: DN301044	
6. AUTHOR(S) P. A. Shoemaker, C. G. Hutchens, S. B. Patil		8. PERFORMING ORGANIZATION REPORT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Command, Control and Ocean Surveillance Center (NCCOSC) RDT&E Division San Diego, CA 92152-5001		10. SPONSORING/MONITORING AGENCY REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Office of Naval Research 800 N. Quincy Street Arlington, VA 22217		11. SUPPLEMENTARY NOTES	
12a. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution is unlimited.		12b. DISTRIBUTION CODE	
13. ABSTRACT (Maximum 200 words) One reason for the recent resurgence of interest in neural network-like computational models has been the prospect of compact and fast implementations of these networks in integrated circuit form. While analog implementation offer considerable advantages with regard to speed and density, their precision and noise immunity are important concerns. Some researchers (e.g., Mead and coworkers) have built analogues of biological structures for early sensory processing, and they have emphasized that tolerance of noisy and imprecise components is a natural emergent feature of these networks. However, the ways in which "higher" or "cognitive" functions might be learned and computed with such components for the most part remains unknown. In addition, learning itself remains problematic in analog circuitry. Means proposed for long-term, modifiable analog weight storage (e.g., floating-gate MOS devices) are sensitive, difficult to control, and of limited precision. We have chosen to implement a model of olfactory processing proposed by Granger, Lynch, and Ambros-Ingerson, which we believe to be an instructive paradigm for computation in a learning system with low-precision weights and weight changes. The model has been shown capable of performing a hierarchical clustering of vectors on its input space. This capability is of potential interest for a range of applications, from automatic target recognition (ATR) to surveillance and detection. The network requires only coarse-valued weights (three to five bits resolution) and its operation relies on the statistical properties of large assemblages of sparsely interconnected neurons, rather than high precision processing. In addition, clustering capability is acquired by an unsupervised coactivity-based learning rule that requires only increments and admits a single parallel implementation. The fact that the network can learn to extract structure from its input environment in an unsupervised fashion is of general interest for the advancement of autonomous or "smart" systems with a broad range of defense and space applications.			
14. SUBJECT TERMS synchronous analog granger/lynch olfactory		15. NUMBER OF PAGES	
17. SECURITY CLASSIFICATION OF REPORT UNCLASSIFIED		18. SECURITY CLASSIFICATION OF THIS PAGE UNCLASSIFIED	
19. SECURITY CLASSIFICATION OF ABSTRACT UNCLASSIFIED		20. LIMITATION OF ABSTRACT SAME AS REPORT	

DTIC
ELECTE
JUN 10 1993
S A D

93 6 6 6

93-12985
93-12985

Published in COMAC 1992 Digest of Papers, Vol. 18, 1992.

UNCLASSIFIED

21a NAME OF RESPONSIBLE INDIVIDUAL P. Shoemaker	21b TELEPHONE (include Area Code) (619) 553-5385	21c OFFICE SYMBOL Code 552																				
Empty space for notes or additional information																						
<table border="1"> <tr> <td colspan="2">Accession For</td> </tr> <tr> <td>NTIS CR&I</td> <td><input checked="" type="checkbox"/></td> </tr> <tr> <td>DTIC TAB</td> <td><input type="checkbox"/></td> </tr> <tr> <td>Unannounced</td> <td><input type="checkbox"/></td> </tr> <tr> <td colspan="2">Justification</td> </tr> <tr> <td colspan="2">By</td> </tr> <tr> <td colspan="2">Distribution</td> </tr> <tr> <td colspan="2">Availability Codes</td> </tr> <tr> <td>Dist</td> <td>Avail and/or Special</td> </tr> <tr> <td>A-1</td> <td></td> </tr> </table>			Accession For		NTIS CR&I	<input checked="" type="checkbox"/>	DTIC TAB	<input type="checkbox"/>	Unannounced	<input type="checkbox"/>	Justification		By		Distribution		Availability Codes		Dist	Avail and/or Special	A-1	
Accession For																						
NTIS CR&I	<input checked="" type="checkbox"/>																					
DTIC TAB	<input type="checkbox"/>																					
Unannounced	<input type="checkbox"/>																					
Justification																						
By																						
Distribution																						
Availability Codes																						
Dist	Avail and/or Special																					
A-1																						

DTIC QUALITY INSPECTED 2

AN ANALOG CLUSTERING NETWORK FROM A BIOLOGICAL MODEL

P.A. Shoemaker, C.G. Hutchens*, S.B. Patil*

Code 552, NRaD
San Diego, CA 92152-5000

*Permanent Address:

Electrical and Computer Engineering Dept.
Oklahoma State University
Stillwater, OK 74078

This work supported by the Office of Naval Research
(Work Order # N0001492WX24141)

Introduction

One reason for the recent resurgence of interest in neural network-like computational models has been the prospect of compact and fast implementations of these networks in integrated circuit form. While analog implementations offer considerable advantages with regard to speed and density, their precision and noise immunity are important concerns. Some researchers (e.g., Mead and coworkers) have built analogues of biological structures for early sensory processing, and they have emphasized that tolerance of noisy and imprecise components is a natural emergent feature of these networks. However, the ways in which "higher" or "cognitive" functions might be learned and computed with such components for the most part remains unknown. In addition, learning itself remains problematic in analog circuitry. Means proposed for long-term, modifiable analog weight storage (e.g., floating-gate MOS devices) are sensitive, difficult to control, and of limited precision.

We have chosen to implement a model of olfactory processing proposed by Granger, Lynch, and Ambros-Ingerson, which we believe to be an instructive paradigm for computation in a learning system with low-precision weights and weight changes.^{1,2} The model has been shown capable of performing a hierarchical clustering of vectors on its input space. This capability is of potential interest for a range of applications, from automatic target recognition (ATR) to surveillance and detection. The network requires only coarse-valued weights (three to five bits resolution) and its operation relies on the statistical properties of large assemblages of sparsely interconnected neurons, rather than high precision processing. In addition, clustering capability is acquired by an unsupervised coactivity-based learning rule that requires only increments and

admits a simple parallel implementation. The fact that the network can learn to extract structure from its input environment in an unsupervised fashion is of general interest for the advancement of autonomous or "smart" systems with a broad range of defense and space applications.

The Model

The interested reader is referred to the work of Granger et al. for details of the olfactory model.^{1,2} Herein we give an abbreviated, qualitative summary of the model in engineering terms. The system accepts a vector input with components of like algebraic sign. This input is subject to a form of normalization which constrains total sum-magnitude of the processed signals to on the order of 20% of maximum. Each normalized component is then "thermometer-coded," or quantized and represented by the number of active two-state cells within a group ("glomerulus") of such cells associated with that component. The outputs of these ("mitral") cells project via a randomly interconnected, sparse (i.e., on the order of 10% full) weight matrix to a second set of ("piriform") cells, which are arranged in winner-take-all subnetworks. The most strongly stimulated piriform cell in each subnetwork activates, and the sparse pattern of activity of the piriform cells represents the output of the system.

The active piriform cells subsequently send inhibitory feedback to the glomeruli via correlationally-developed (Hebbian) interconnections, so that inhibition is strongest for those input components most responsible for the piriform activation. The input is resampled, combined with this inhibition, and re-normalized, resulting in a pattern of mitral activity in which initially large components are squelched and secondary components are expressed more strongly.

The new pattern of mitral activity is fed forward to the piriform cells and results in a new pattern of piriform activity. This cycle is typically repeated a number of times.

When the system is in the learning mode, the weights of interconnections between active mitral and winning piriform cells are incremented at each cycle of activity. As a consequence of this learning, the piriform output codes for input vectors which are sufficiently similar, or clustered in the input space, tend to develop a high degree of overlap or become identical. In addition, with the multiple sampling and feedback inhibition, the inputs are clustered into successively finer subclusters or categories (indicated by identical or nearly identical piriform output codes) based on secondary and tertiary characteristics.

Implementation

We propose a direct analog CMOS implementation of this model. This network would operate synchronously with regard to the resampling cycle required for hierarchical clustering, with feedforward and feedback subphases. However, computations of neuronal states would be analog, asynchronous, and carried out in parallel. Current mode design techniques have been employed. Floating-gate weight storage and on-chip, parallel learning are proposed.

The normalization required by the model can be achieved with a circuit analogous to vector automatic gain control, with saturating nonlinearity applied to each component. Thermometer-coding is performed by a circuit analogous to the input stage of a parallel A/D converter. On the piriform side, winner-take-all subnetworks are implemented using circuits with global feedback.³

For "synaptic" weights, we propose the use of single floating-gate transistors whose transconductance is modulated by charge on the floating gate. We propose to implement the sparse, random weight matrix with a one-to-one correspondence of the number of weighting elements to number of synapses in the model, with mask-programmable connection of input and output lines allowing establishment of pseudorandom connectivity.

To implement feedback inhibition of the bulb by the piriform, we propose a time-duplex scheme. Because the correlationally-developed feedback interconnections arise as a direct consequence of the given feedforward connectivity, the same inhibitory effect can be obtained by

using the transpose of the sparse weight matrix to compute the inhibition. Physically, a single weight matrix would be driven bidirectionally in two phases, to successively compute both feedforward excitation and feedback inhibition. To allow this bidirectionality, interface is made to the weight matrix via type-II current conveyors.⁴

For individual weights, the control logic for the coactivity-based learning rule corresponds to a simple AND function; taken in parallel it may be regarded as a Boolean outer product. This can be implemented on crossbars running through the weight matrix using simple switches which are controlled by the neuron states and which route programming voltages to writing circuitry for the floating-gate weights.

The building-block circuits required for the implementation described above have been fabricated using the MOSIS and Orbit Semiconductor Foresight prototyping services. DC functionality was established experimentally for most, with AC or transient response estimated from SPICE simulations. We present circuit designs and test and simulation results in poster illustrations, including results from a variety of candidates for floating-gate weight circuits which were fabricated in the standard processes. A simple scheme to compensate for the strong nonlinearity of the floating gate charging mechanisms is described. Plans for a network with on the order of 35,000 weights are also detailed.

References

1. J. Ambros-Ingerson, R. Granger, and G. Lynch, "Simulation of paleocortex performs hierarchical clustering," *Science* vol. 247, pp. 1344-1348, 1990.
2. R. Granger, J.A. Ambros-Ingerson, P. Anton, and G. Lynch, "Unsupervised perceptual learning: a paleocortical model," Ch. 5 in *Connectionist Modeling and Brain Function*, S. Hanson and C. Olsen, Eds., MIT Press, Cambridge, MA, 1990.
3. J. Lazzaro, S. Ryckebusch, M.A. Mahowald, and C.A. Mead, Winner-take-all networks of $O(N)$ complexity. CIT Technical report Caltech-CS-TR-21-88, 1989.
4. A.S. Sedra and G.W. Roberts, "Current conveyor theory and practice," Ch. 3 in *Analogue IC Design: The Current-Mode Approach*, C. Toumazou, F.J. Lidgey, and D.G. Haigh, Eds., Peregrinus, London, 1990.